SMART-GRID BASED PEER-TO-PEER ENERGY TRADING MODEL

Dissertation submitted to
Visvesvaraya National Institute of Technology, Nagpur
in partial fulfillment of the requirements for the award of
the degree

Master of Technology
in
Integrated Power System

by

Nidhi S. Fukatkar (MT23IPS006)

under the guidance of

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Visvesvaraya National Institute of Technology
Nagpur 440010 (India)

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Declaration

I, Nidhi S. Fukatkar, hereby declare that this dissertation titled **"Smart-grid based Peer-to-Peer Energy Trading Model"** is carried out by me in the Department of Electrical Engineering of Visvesvaraya National Institute of Technology, Nagpur. The work is original and has not been submitted earlier whole or in part for the award of any degree/diploma at this or any other Institution / University.

Nidhi

Nidhi S. Fukatkar
Date: 30/05/25

Certificate

This to certify that the dissertation titled **"Smart-grid based Peer-to-Peer Energy Trading Model"** is submitted by Ms. Nidhi S. Fukatkar in partial fulfillment of the requirements for the award of the degree of Master of Technology in Electrical Engineering with specialization Integrated power System, VNIT Nagpur. The work is comprehensive, complete and fit for final evaluation.

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ABSTRACT

The growing integration of renewable energy sources (RES) and the decentralization of power systems have given rise to Peer-to-Peer (P2P) energy trading frameworks within smart grids. This study proposes a decentralized P2P energy trading model that incorporates price differentiation**,** network power loss**,** network usage charges**,** and carbon emission penalties**,** aiming to enhance social welfare while promoting environmentally responsible and grid-feasible operations.

Initially, a lagrangian-based decentralized optimization framework is developed, where prosumers and consumers independently optimize their trading strategies based on individual utility and cost functions. Network losses and locational constraints are embedded into the economic optimization through Power Transfer Distance (PTD), allowing differentiation in trading prices and more realistic modelling of power exchange. Additionally, a carbon emission penalty function is integrated using a logarithmic form to ensure smooth market response and promote green energy choices. Simulation results using the IEEE 9-bus system show that incorporating price differentiation improves welfare by 49%, while carbon penalties promote sustainability with minimal welfare maximization.

This study proposes a decentralized peer-to-peer (P2P) energy trading framework incorporating renewable energy integration, carbon emission penalties, and dynamic pricing mechanisms using Lagrange multipliers. The system considers multiple producers—one of which is a renewable generator—and multiple consumers within an IEEE 9-bus inspired environment. The model optimizes energy allocation between producers and consumers based on utility maximization and cost minimization, while penalizing carbon emissions beyond permissible caps..

Simulation results demonstrate that the proposed approach achieves a significant improvement in social welfare while reducing carbon emissions compared to traditional centralized dispatch. The inclusion of renewable sources not only enhances environmental sustainability but also contributes to the economic welfare of the system by lowering overall generation costs.

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ABBREVIATIONS

RES: Renewable energy source

P2P: Peer to peer

DER: Distributed energy resource

PTDF: Power transfer distribution factors

NAC: Nodal access charges

l: index of producer

m: index of consumer

G_l: Set of producer

Q_m: Set of consumer

K_m: Network utility charge (NUC)

γ: Producer loss coefficient

EF_l: Emission faactor

FiT: Feed in Tariff

Uj: Utility of consumer

G(l,m): Total power generated

δ_m : Initial willingness to pay

e_m : Diminishing marginal utility

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CHAPTER 1

OVERVIEW

1.1 INTRODUCTION

The global shift towards sustainable and decentralized energy systems is significantly transforming the power sector. Local end user involvement has increased substantially due to integration of renewable energy sources (RES), such as, solar panels. Programs like feed in tariff (FiT) empowers the prosumers who owns solar panels, battery storage devices, electric motor vehicles. Prosumers are individuals or entities that generate and consume electricity to inject their surplus energy into grid. The concept of peer to peer (P2P) energy trading, where prosumers and consumers can directly exchange energy within a localized market is presented.

Traditional markets are centralized. This centralized energy systems rely on large utility companies that control generation, distribution and pricing. Consumers, thus have very little flexibility in choosing their energy sources. P2P energy trading allows decentralized energy systems. Decentralized networks allow prosumers to generate, sell and buy electricity directly from each other, reducing dependency on utility.

Traditional markets have energy prices that are dictated by utilities, often including transmission fees, taxes and operational costs. P2P energy trading eliminates intermediaries, allowing consumers to purchase energy at competitive rates while producers earn better returns on their surplus electricity.

In traditional energy markets, energy is transmitted over long distances, leading to energy losses and inefficiencies. In P2P energy trading, localized energy exchanges minimize transmission losses, improving grid efficiency and reducing strain on infrastructure.

Traditional markets prioritizes conventional power plants, slowing adoption of renewables. P2P energy trading encourages renewables like the use of solar, water and other distributed energy sources (DER), accelerating transition to sustainable energy.

In traditional markets, consumers have limited control over their energy choices and pricing, whereas, in P2P energy trading, consumers can choose their energy sources, negotiate prices, and participate in dynamic marketplace.

Centralized grids are vulnerable to failures, leading to widespread blackouts. In P2P energy trading, centralized grids are vulnerable to failures, leading to widespread blackouts.

Traditional Markets are heavily regulated, often restricting independent energy trading. Governments are exploring new policies to support decentralized energy markets, fostering innovation and competition.

Decentralized energy exchanges lower dependency on fossil-fuel-based power plants, contributing to a cleaner energy future.

Peer-to-peer (P2P) energy trading is revolutionizing the traditional centralized energy markets by offering a decentralized, transparent, and consumer-driven approach to electricity exchange.

1.2 LITERATURE SURVEY

Peer-to-peer (P2P) energy trading has gained considerable attention as a promising approach to reshape conventional electricity markets. Traditional energy systems rely on a centralized structure where a utility company governs production, distribution, and pricing. In contrast, P2P energy trading empowers prosumers—individuals or entities capable of both producing and consuming electricity—to trade surplus energy directly with other users.

Early implementations of P2P models primarily focused on centralized methods, where a central coordinator supervises all transactions and manages energy flows. Although this structure facilitates oversight and market stability, it introduces privacy concerns and restricts individual autonomy. Researchers have identified this limitation and proposed decentralized models that operate without centralized supervision.

In centralized models, the energy exchange is governed by a supervisory entity or market operator. Studies such as those in [1] and [2] emphasize that although this system ensures regulatory compliance and ease of monitoring, it limits participants' control over decision-making. Moreover, the privacy of market actors may be compromised due to data aggregation and sharing.

To address these concerns, decentralized trading models have been proposed, as discussed in [3] and [4]. These frameworks allow independent transactions between prosumers without centralized mediation, enhancing transparency and privacy. Decentralized architectures also enable bilateral negotiations and dynamic pricing mechanisms tailored to individual preferences.

The integration of distributed control strategies like consensus algorithms [5] and dual decomposition techniques [6] has enhanced the feasibility of decentralized systems. These methods allow participants to adjust trading behaviour autonomously while maintaining system-wide equilibrium.

Pricing strategies play a critical role in P2P energy markets. Different models have been proposed to balance supply and demand effectively and fairly. For instance, studies have explored dynamic pricing [7], flat-rate pricing [8], and auction-based methods [9], [10]. Game-theoretic approaches have also been employed to model strategic interactions among agents and optimize collective welfare [11], [12].

One emerging area in pricing research is price differentiation, where producers offer variable pricing depending on buyer preferences, location, or network constraints. This enables participants to trade energy based on individualized needs and enhances market flexibility. Price differentiation also addresses the problem of single-price uniformity, which may not reflect varying production costs or consumer valuations.

Beyond economic optimization, technical constraints such as line losses, network congestion, and nodal access charges (NAC) significantly affect the viability of P2P systems. Some researchers [13], [14] have incorporated these constraints into their models, recognizing that physical power flow limitations influence both cost and feasibility.

Models that consider power transfer distribution factors (PTDF) are particularly relevant in distributed settings, as they allow for estimating the impact of each transaction on the transmission network. These considerations are essential for realistic simulations and for ensuring that P2P trading platforms can operate reliably under real-world conditions.

In [15], distributed optimization algorithm is used aiming to maximize the social welfare. A decentralized P2P energy trading model that takes price differential in the smart grid into account is presented in this study [16]. In order to enhance the reliability of such energy trading systems and boost revenue through surplus energy, the paper proposes a P2P network with a rule-based algorithm for dynamic pricing mechanisms that take peer preferences into account when trading energy and can manage various load combinations [17].

A recent trend in the literature involves integrating environmental sustainability into P2P energy trading models. Carbon emission penalties and renewable energy incentives have been introduced to guide trading behaviors toward greener alternatives. For example, emission-aware cost functions and carbon caps are used to penalize polluting producers, encouraging a shift to low-carbon generation.

At the same time, multiple studies have emphasized social welfare maximization as a key objective. Rather than focusing solely on cost minimization or individual profits, these models aim to enhance the collective well-being of all market participants. Metrics such as net consumer utility and producer profit, adjusted for environmental penalties, are commonly used to quantify social welfare.

Although extensive work exists on P2P trading architectures, pricing models, and network constraints, few studies have unified all these elements into a single optimization framework. Specifically, the combination of price differentiation, network usage charges, and carbon emission penalties in a decentralized P2P market remains underexplored.

Peer-to-peer (P2P) energy trading in an electrical distribution network allows various participants to share benefits while effectively integrating distributed renewable energy sources. Additionally, the participation of hybrid renewable energy systems, such as

photovoltaic (PV) systems and wind turbine generators (WTGs), is crucial for improving energy flexibility and diversity in active distribution networks. In this study, the alternating direction method of multipliers (ADMM) is utilized to develop a fully decentralized P2P energy trading strategy, where self-motivated participants achieve optimal trading outcomes iteratively through multilateral discussions [23].

Peer-to-peer (P2P) energy trading is a developing solution for enhancing energy distribution in microgrids that relies on the use of local energy resources like solar panels and energy storage systems. It is anticipated that energy networking will effectively balance energy at a local level and manage the increasing penetration of distributed energy resources (DER) in the future. Implementing energy exchange technology within the microgrid framework will create a flexible electricity market among peers, meeting consumer demands with renewable energy sources. This research simulates a P2P energy trading system featuring five households, each equipped with solar panels, energy storage, and energy loads [24].

The incorporation of Renewable Energy (RE) at the residential level is a significant focus for researchers, and trading excess energy within a microgrid proves to be more efficient than relying on battery storage, ultimately lowering ongoing costs. Additionally, to enhance reliability, this trading can be combined with blockchain technology in a peer-to-peer (P2P) network. In light of this, the paper presents a case study that demonstrates a scheme for RE trading within a microgrid, utilizing a blockchain-based P2P network [25].

The liberalization of the electricity market and the decentralization of regions have advanced in relation to the reliable use of electricity, while the adoption of renewable energy sources is being encouraged as a measure against global warming. However, the output from renewable energy can vary significantly depending on the time and location, leading to situations where power generation is either excessive or insufficient, which hinders the establishment of a stable regional power system. We suggest innovative decentralized peer-to-peer (P2P) negotiation approaches to optimize the excess and deficiency of energy within a region through the sharing of local renewable resources, and we assess these approaches using multi-agent simulations [26].

1.3 OBJECTIVE OF STUDY

1) To design the decentralized market clearing algorithm for energy pricing strategy by considering carbon penalty for P2P energy trading is the major focus of the work. The objective of this study is also to increase the welfare of the community and to implement model in a more practical way.
2) The objective of this study is to develop and evaluate a decentralized peer-to-peer (P2P) energy trading mechanism in an IEEE 9-bus power system that enhances social welfare by optimizing both consumer utility and producer cost. To achieve this by integrating renewable source instead of conventional generator. The model aims to monitor and improve social welfare across iterations.

1.4 THESIS ORGANIZATION

There are five different chapters in this thesis. Chapter 1 provides the overview, the context and the inspiration for this study.

1. Chapter 2 consists of P2P trading with network limitations and carbon penalty.
2. Chapter 3 consists of P2P trading with renewable producer.
3. Chapter 4 covers the conclusion for all chapters.

CHAPTER 2

P2P ENERGY TRADING WITH NETWORK LIMITATIONS AND CARBON PENALTY

2.1 INTRODUCTION

Peer-to-Peer (P2P) Energy Trading, a decentralized approach that allows individuals and businesses to buy and sell electricity without relying on traditional utility companies. However, while P2P trading presents opportunities for cost-effective, sustainable, and democratized energy distribution, it is not without challenges. One of the most critical barriers to its widespread adoption is network limitations, including grid congestion, infrastructure constraints, and technological compatibility issues. These challenges can affect the efficiency, reliability, and scalability of decentralized trading systems, necessitating advanced optimization techniques to ensure seamless energy distribution.

Additionally, as governments and policymakers intensify their efforts to combat climate change, carbon penalties have become a crucial regulatory mechanism. These penalties impose financial costs on entities that generate or trade carbon-intensive electricity, incentivizing the adoption of cleaner energy sources. Within the P2P trading framework, integrating carbon pricing mechanisms and emissions tracking can play a key role in promoting sustainability while maintaining economic feasibility.

This chapter explores the fundamental principles of P2P energy trading**,** its network constraints, and the impact of carbon penalties on decentralized power markets. By analysing these factors, we aim to assess the viability of P2P trading as a scalable, efficient, and environmentally responsible alternative to traditional energy exchange models.

2.2 SYSTEM MODEL

In this study, a smart grid is considered. A smart grid's decentralized P2P energy trading market involves several players. The smart grid has an electrical network for energy transfer and a communication network for information exchange between players.

A set of producers $G_l = \{1,...,nG\}$ with an index $l \in P_l$ and a smart grid collection of customers with index $m \in Q_m$, where $Q_m = \{1,...,nQ\}$. $N = nG+nQ$ is the total number of players. In this, a one-hour market period in the P2P market is examined. The terms "power" and "energy" are equivalent when considering the one-hour market period. Every participant behaves independently during this period and makes an effort to maximize its well-being. The framework for such type of market is shown in Fig 2.1.

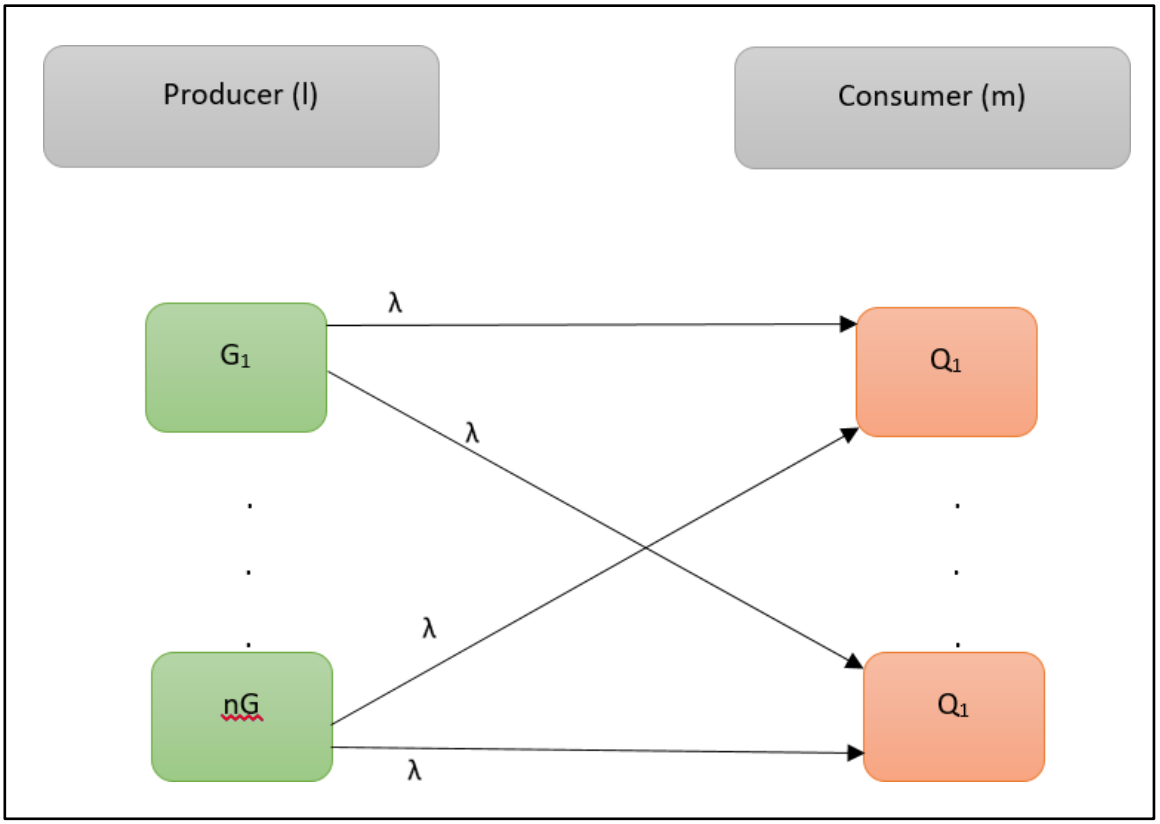

Figure 2.1: Framework of P2P energy market

2.2.1 System overview

The components of the system are as follows:

Prosumers are entities that have the capacity to produce and use power. Customers that solely use power and engage in the market to purchase energy at the best possible prices. Energy providers are traditional power plants that contribute to the system's overall energy supply.

A framework for decentralized P2P energy trading is introduced. This framework comprises of prosumers and consumers. Each prosumer can sell excess energy to other prosumers based on local use and generation. Energy transactions are both economically advantageous and practically viable.

The electrical network includes participants in the energy market. Energy trading is subject to technical limitations since they must use this network for trade. Since they use the electrical network to transport energy, market participants in P2P schemes are responsible for paying for network constraints like NPL(network power loss) and NUC(network usage charge). Producers should be given this NPL in order to maintain a balanced operation. The following is the formula for NPL that producer *l* incorporates after exchanging energy with customer *m*:

$$W_{lm}(G_{lm}) = \gamma_l G_{lm}^2 \tag{2.1}$$

The network parameter and network structure determine the producer *l* loss coefficient, orγ_l [13]. The energy exchanged between producer *l* and consumer *m* is denoted by G_{lm}.

The expense which facilitates energy transactions between prosumers through the distribution network is covered by NUC. For consumer *m*, the NUC is written as follows:

$$K_m = \sum_{l \in P_l} \omega \Delta_{lm} Q_{lm} \tag{2.2}$$

In this case, ω is the NUC for moving one unit energy per unit of distance.

The quantity of power that consumer *m* purchased from producer *l* is denoted by Q_{lm}. The electrical distance between producer *l* and consumer *m* is shown by the symbol Δ_{lm}.

The electrical distances between producers and consumers are estimated using the Power Transfer Distance (PTD). The comprehensive PTD calculation method is given in [18].

Price differentiation pertains to a market system in which electricity prices are not consistent but differ among various participants. This promotes effective energy distribution and user-focused trading in decentralized markets. By supporting P2P with price differentiation, which offers different pricing for every transaction, the energy market should also respect the wishes of its participants. By selecting an option based on their pricing, price differential incentivizes consumers to meet their energy needs. Using lagrangian method price differentiation is achieved [16].

2.2.2 Consumer's social welfare

The perceived benefit of using the energy that has been purchased from producers influences the behaviour of consumers. To simulate customer welfare and desires, the function of utility [11,12] of consumers [1] is given below. The sensitive information of the m^{th} consumer is represented by δ_m and e_m. Energy is demanded by consumers from various producers. It must fall between the maximum and minimum limits. $G_{d,m}$ is the total of the energy that consumer m demands from producer l.

$$R_m\left(G_{d,m}\right)=\begin{cases}\delta_m G_{d,m}-\frac{1}{2}e_m G_{d,m}^2 & ;0\le G_{d,m}\le\frac{\delta_m}{e_m}\\ \frac{\delta_m^2}{2e_m} & ;G_{d,m}\ge\frac{\delta_m}{e_m}\end{cases} \tag{2.3}$$

$$G_{d,m}=\sum_{l=1}^{nG}G_{d,ml}\ ;\ G_{d,m}^{\min}\le G_{d,m}\le G_{d,m}^{\max} \tag{2.4}$$

The consumer's demand must fall between minimum and maximum limits, this is to ensure the control limits. Exceeding the maximum demand can overload the electrical grid, causing voltage fluctuations, frequency instability, and even system failures. If the load demand is too low, it may lead to inefficient operation of power plants, affecting grid stability.

Electrical infrastructure, including transformers, transmission lines, and generators, has a rated capacity. Exceeding this can cause overheating, insulation breakdown, and potential damage. Operating below a certain threshold may result in underutilization of equipment, leading to inefficiencies and increased maintenance costs.

The sum of all potential trades or the consumer's overall welfare, is stated as

$$W_m = \sum_{l=1}^{nG} (R_m(G_{d,ml}) - \lambda_{lm}(G_{d,ml}) - K_m) \tag{2.5}$$

Where $R_m(Gd_{,m})$ is the utility of consumer. λ_{lm} is the traded energy price between producer l to consumer m.

2.2.3 Producer's social welfare

A cost function that is quadratic in nature is used to formulate the cost of operation that producer l spends on consumer m. The cost function [13] is shown as

$$\Psi_{lm}(G_{g,lm}) = (a_l G^2_{g,lm} + b_l G_{g,lm} + c_l) + (\alpha_l G^2_{g,lm} + \eta_l G_{g,lm} + \omega_l) \tag{2.6}$$

First and second term represent fuel cost and emission cost respectively. The total energy given by producer l to consumer m is energy produced by each producer ($G_{g,l}$).

$$G_{g,l} = \sum_{m=1}^{nQ} G_{g,lm} \;\; ; \; G_{g,l}^{\min} \leq G_{g,l} \leq G_{g,l}^{\max} \tag{2.7}$$

The overall welfare of producer *l* is determined as [16],

$$W_l = \sum_{m=1}^{nQ} (\lambda_{lm}(G_{g,ml}) - \Psi_{lm}(G_{g,lm})) \tag{2.8}$$

The money received from providing energy to consumers is indicated by the first phrase, while the equal energy cost is indicated by the second.

Environmental laws such as carbon emission limitations have an impact on each producer's social welfare in addition to production costs and energy sales earnings. To deter excessive emissions, a penalty fee is imposed if a producer's carbon emissions surpass the predetermined carbon cap. The carbon cap is the maximum carbon emission limit.

The total carbon emission [19] for producer *l* is given as

$$E_l = (EF_l) G_{g,l} \tag{2.9}$$

Where EF_l is the emission factor (tons of CO_2 per MWh) and $G_{g,l}$ is the total generation of producer *l*. If the emissions exceed the carbon cap Cap_l, a penalty function is applied as,

$$Penalty_l = C_p (\ln(1 + \max(0, E_l - Cap_l))) \tag{2.10}$$

Here, C_p is the carbon price (in $ per ton CO_2), and a logarithmic function ensures smooth penalty growth to avoid market shocks.

Thus, the producer's welfare for energy traded with consumer *m*, considering carbon penalties, is given as

$$W_l = \sum_{m=1}^{nQ} (\lambda_{lm}(G_{g,ml}) - \Psi_{lm}(G_{g,lm}) - Penalty_l)$$

(2.11)

The revenue from the sell of energy is represented by first term. Second term represents the cost function while third term imposes penalty for exceeding cap_i thus integrating environmental sustainability.

2.3 OBJECTIVE FUNCTION

The goal of the decentralized P2P energy trading optimization problem is to maximize the overall social welfare while enacting a $Penalty_l$ to encourage greener energy trades. The formulation of the overall objective function is as follows:

$$\max_{(G_{d,ml}, G_{g,lm})} \left[\sum_{m=1}^{nQ} W_m + \sum_{l=1}^{nG} W_l \right] \tag{2.12}$$

$$s.t.\ G_{g,lm} = G_{d,ml},\ G_{d,l}^{min} \le G_{d,l} \le G_{d,l}^{max},\ G_{g,l}^{min} \le G_{g,l} \le G_{g,l}^{max} \tag{2.13}$$

Where, W_m is consumers welfare and W_l is producers welfare with $Penalty_l$.

The objective of optimization is to determine the balance between supply and demand among producers and consumers while setting energy trading prices to achieve maximum social welfare. At all times, the constraint of power balance between producer production and consumer consumption should met.

Using a decentralized optimization approach, all market participants' ideal traded energy values and associated energy prices are estimated. According to the following definition, the Lagrangian function for the optimization problem [9] with constraints [10].

$$
\begin{aligned}
L\left(G_{g,lm},G_{d,ml},\lambda_{lm},\chi_l^{\min},\chi_l^{\max},\chi_m^{\min},\chi_m^{\max},\right) &= \sum_{m=1}^{nQ}\sum_{l=1}^{nG} R_m\left(G_{d,ml}\right) - \sum_{l=1}^{nG}\sum_{m=1}^{nQ} \lambda_{lm}(G_{g,ml}) \\
&+ \sum_{l=1}^{nG}\sum_{m=1}^{nQ} \lambda_{lm}\left(G_{g,lm}-G_{d,ml}\right) + \sum_{m=1}^{nQ}\chi_m^{\min}\left(G_{d,m}-G_{d,m}^{\min}\right) + \sum_{m=1}^{nQ}\chi_m^{\max}\left(G_{d,m}^{\max}-G_{d,m}\right) \\
&+ \sum_{l=1}^{nG}\chi_m^{\min}\left(G_{g,m}-G_{g,m}^{\min}\right) + \sum_{l=1}^{nG}\chi_m^{\max}\left(G_{g,m}^{\max}-G_{g,m}\right)
\end{aligned}
\tag{2.14}
$$

Where λ_{lm}, χ_l^{min} ,χ_l^{max} ,χ_m^{min} ,χ_m^{max} denote Lagrangian multipliers [10]. The market clearing price for P2P energy transactions between producer *l* and consumer *m* to keep supply and demand balanced is represented by λ_{lm}. This method uses lagrangian multiplier to calculate the lagrangian function's derivative in order to determine the dual variable. The following are the lagrangian multiplier updated guidelines,

$$
\lambda_{lm}^{k+1} = \left\lceil \lambda_{lm}^{k} - \rho\left(G_{g,lm}^{k} - G_{d,ml}^{k}\right) \right\rceil^{+} \tag{2.15}
$$

$$
\chi_l^{\min,k+1} = \left\lceil \chi_l^{\min,k} - \rho\left(G_{g,l}^{k} - G_{g,l}^{\min,k}\right) \right\rceil^{+} \tag{2.16}
$$

$$
\chi_l^{\max,k+1} = \left\lceil \chi_l^{\max,k} - \rho\left(G_{g,l}^{\max,k} - G_{g,l}^{k}\right) \right\rceil^{+} \tag{2.17}
$$

$$\chi_m^{\min,k+1} = \left[\chi_m^{\min,k} - \rho\left(G_{d,m}^{k} - G_{d,m}^{\min,k}\right)\right]^{+} \tag{2.18}$$

$$\chi_m^{\max,k+1} = \left[\chi_m^{\max,k} - \rho\left(G_{d,m}^{\max,k} - G_{d,m}^{k}\right)\right]^{+} \tag{2.19}$$

The step size is denoted by ρ.The symbol for the max(.,0) is [ ]+. During each iteration, the lagrangian splits into separate producer-side and consumer-side sub problems as dual variables are update. The following lists the energy that producers supply and the energy that consumers desire [16].

$$G_{g,lm} = \frac{\lambda_{lm} - b_l - \eta_l - \chi_l^{\max} + \chi_l^{\min}}{2\left(a_l + \alpha_l\right)} \tag{2.20}$$

$$G_{d,ml} = \frac{\delta_m - \lambda_{lm} - \chi_m^{\max} + \chi_m^{\min}}{e_m} \tag{2.21}$$

Producers supply and energy that consumer demands are the two equations as above (2.20) and (2.21), respectively. These equations are obtained from (2.14) by taking the first order derivative. Simillary, the other equations can also be found by taking first order derivative of (2.14).

The following condition serves as the stopping criterion for all participants,

$$\left|\lambda_{lm}^{k+1} - \lambda_{lm}^{k}\right| < \bar{O}_{\lambda}, \quad \left|\chi_l^{k+1} - \chi_l^{k}\right| < \bar{O}_{\chi_l}, \quad \left|\chi_m^{k+1} - \chi_m^{k}\right| < \bar{O}_{\chi_m} \tag{2.22}$$

Here, $\bar{O}$ is a small positive number.

2.4 IMPLEMENTATION

The interactions between producers and consumers during energy trading is depicted in Fig. 2.2.

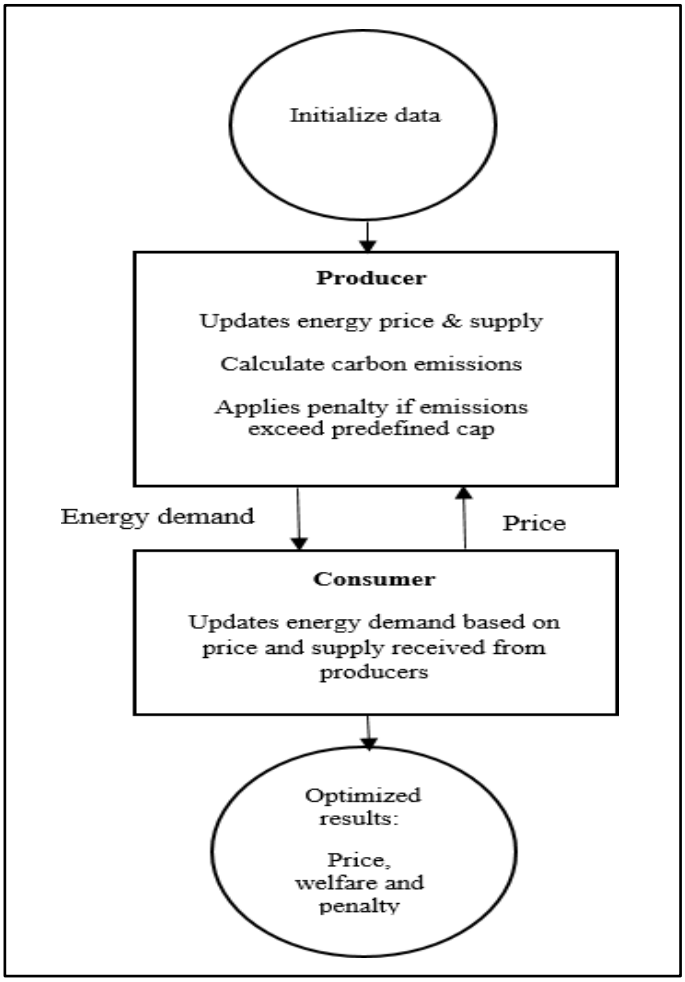

Figure 2.2: Algorithm for market clearing

The foundation of the suggested energy trading paradigm is two-way communication between producers and consumers. Every participant behaves as a logical actor seeking to optimize its own well-being through optimal decision making. To optimize the benefits for all participants in P2P energy trading, producers and consumers need to share key details, including energy pricing and how energy demand is allocated. The implementation steps are as follows:

Step 1: First step is to initialize variable λ, χ_m, χ_l, G_g, $G_{d,}$ E_l, $Penalty_l$

Step 2: Producers adjust their energy pricing and supply levels accordingly using (2.15), (2.16) and (2.17) for different consumers

Step 3: Using (2.20), each producer's energy allocation is updated based on the current energy prices, and the revised prices are then communicated to consumers

Step 4: Updated energy of producer updates the carbon emission and penalty using (2.9) and (2.10)

Step 5: Consumers update (2.18), (2.19) and compute new demand via (2.21) based on current energy prices, then transmit this demand to producers

Step 6: The steps from 2 to 4 is repeated until the stopping criterion is met as in (2.22)

2.5 SIMULATION SETUP AND CASE STUDY

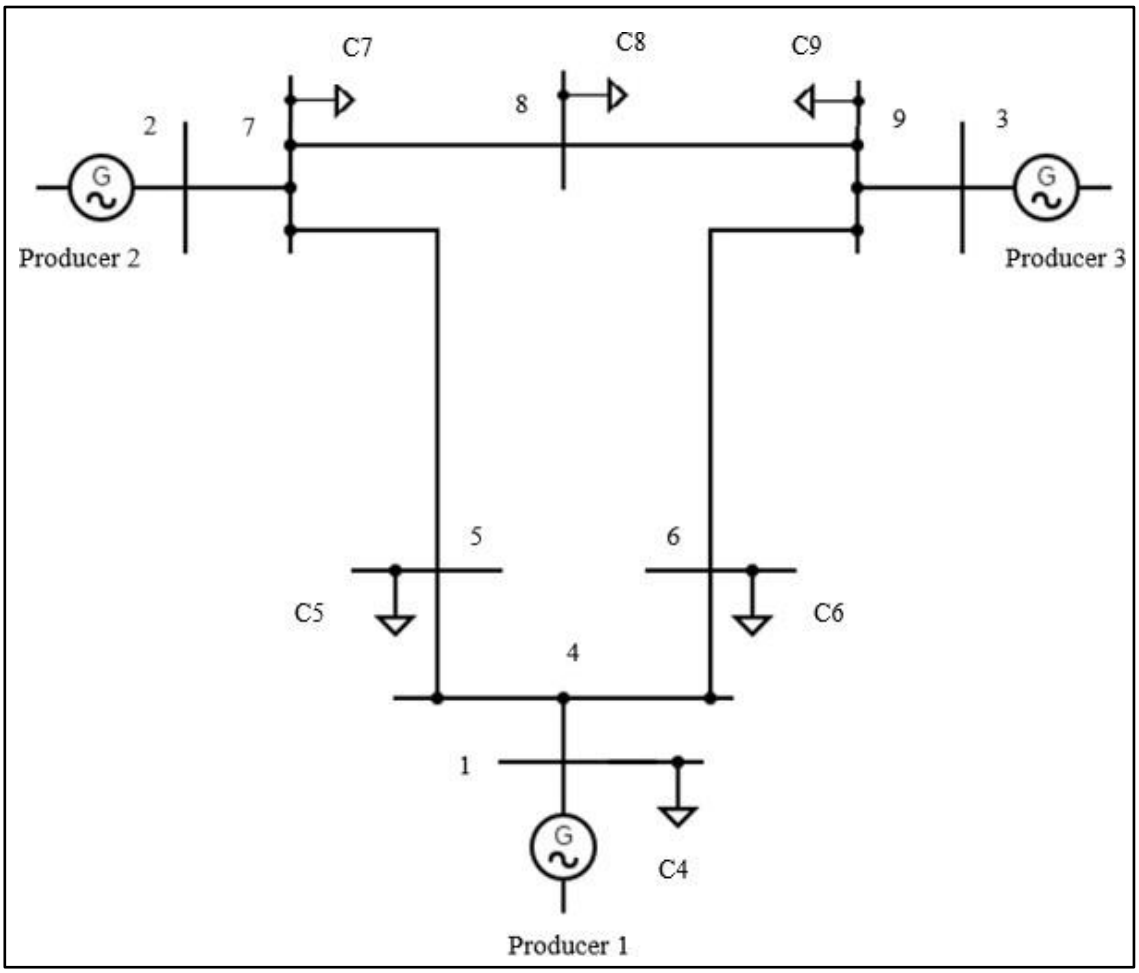

Figure 2.3: IEEE 9-bus system model

IEEE-9 bus system with six consumers and three producers are taken into consideration for case studies of the suggested approach, as seen in figure 2. Producers are situated at buses 1, 2 and 3 in IEEE 9 bus systems, where as consumers are positioned at buses 4 through 9. The sensitive information of producers and consumers are given in Table 1 and Table 2.

For updating the Lagrangian multiplier, a step size of 000.005 is chosen, $\alpha = 0.02$ and $\eta = 0.1$ are taken into consideration as the emission cost factors [16]. EF_i 0.5, 0.6 and 0.4 values are chosen with plants considering oil based plant, oil based plant and natural gas based plant respectively with oil based plants considering efficiency up to

45% and natural gas based plant up to 35% [20]. Carbon price of $30/tons of CO_2 is taken [22]. The carbon caps 120, 100, and 150 tons of CO_2 were selected to reflect varying emission intensities of generators, based on empirical data from IPCC and EPA reports [19]. In this case study, one hour of a normal day is taken into consideration.

Table 2.1: Producer's input parameters

Producer	a_l	b_l	G_{gmin}	G_{gmax}
	($/MWh^2)	***($/MWh)***	***(MWh)***	***(MWh)***
P_1	0.0080	2.25	10	350
P_2	0.0062	4.20	20	290
P_3	0.0075	3.25	15	400

Table 2.2: Consumer's input parameters

Consumer	e_m	δ_m	G_{dmin}	G_{dmax}
	($/MWh^2)	***($/MWh)***	***(MWh)***	***(MWh)***
C_4	00.0720	08.25	060	150
C_5	00.0660	07.90	050	100
C_6	00.0700	07.55	090	145
C_7	00.0550	08.00	060	140
C_8	00.0750	07.75	050	150
C_9	00.0450	08.05	070	170

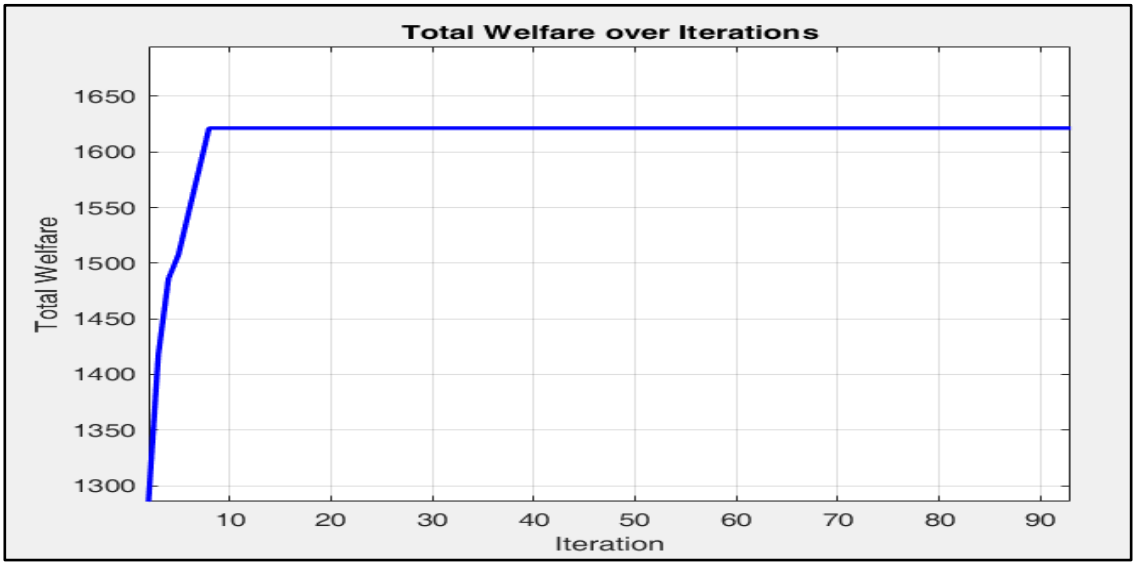

Figure 2.4: Total welfare over iterations

Fig 2.4 illustrates the evolution of total social welfare over successive iterations in the decentralized P2P energy trading algorithm. The iterative approach is essential for achieving an optimal balance between power generation, demand fulfilment, and cost efficiency, particularly when network limitations and carbon penalties are considered. Initially, the welfare value increases sharply as the system adjusts trading prices and power allocations to better match supply with demand. After approximately 10 iterations, the curve begins to settle, indicating that the system has converged to a near solution. This stable convergence reflects that the algorithm successfully maximizes community welfare while accounting for technical and environmental constraints. The iterative nature ensures the robustness and feasibility of the trading mechanism in a decentralized, network-constrained environment.

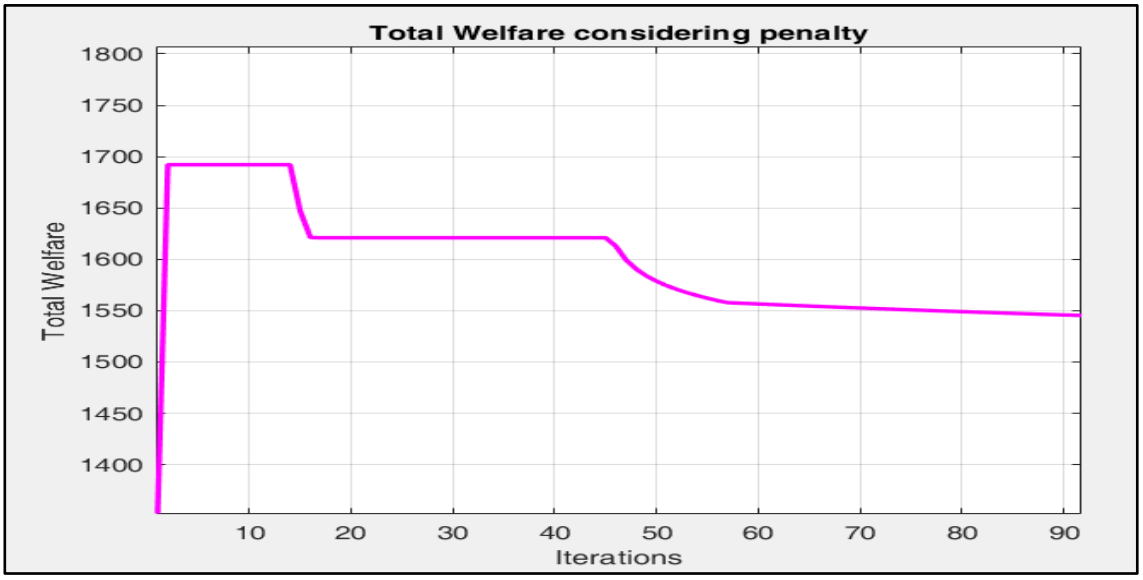

Figure 2.5: Total welfare considering penalty over iterations

Initially, the welfare increases sharply, indicating that the decentralized optimization algorithm quickly converges toward an efficient allocation of power between producers and consumers. By the 10th iteration, the welfare stabilizes around 1630 units, reflecting the effectiveness of the trading strategy in maximizing system-wide utility and minimizing cost under ideal conditions.

While the welfare initially increases, a noticeable decline occurs around the 15th and again near the 50th iteration. This drop signifies the influence of emission penalties on producer profits and consumer costs. The algorithm compensates by adjusting energy allocations to favor greener sources, thereby balancing economic efficiency with environmental responsibility. Eventually, welfare stabilizes around 1550 units, which, while lower than the penalty-free case, represents a more sustainable outcome aligned with carbon reduction goals.

Although, when aggregated the welfare is found to be 1625$ which is increased compared to fig. 2.4 where welfare is 1610$.

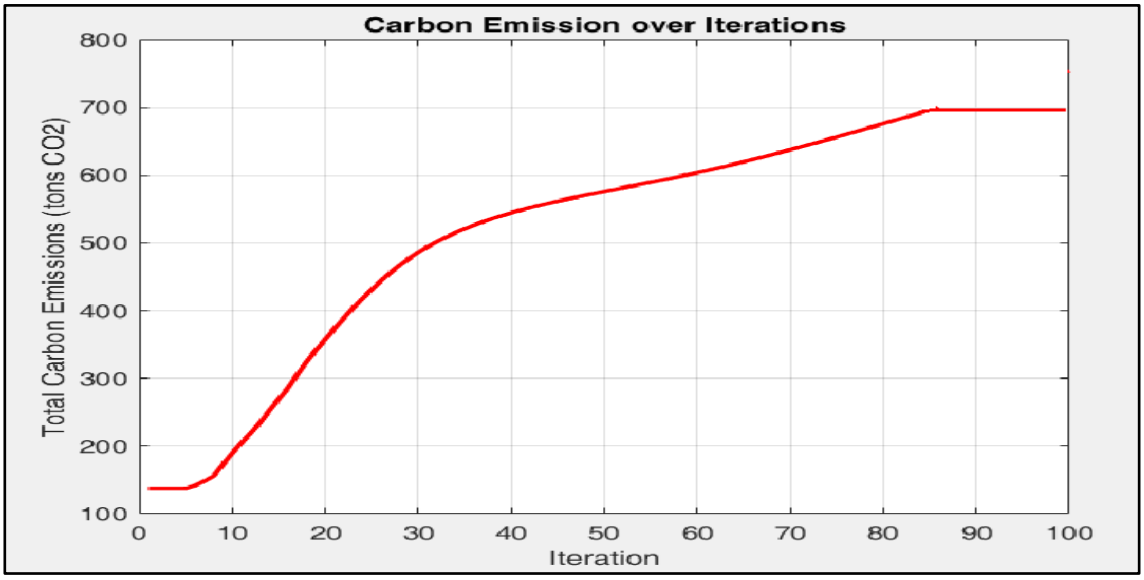

Figure 2.6: Carbon emission over iterations

The graph titled "Carbon Emission over Iterations" illustrates the variation in total carbon emissions (in tons of CO_2) throughout the iterative optimization process of the P2P energy trading model. Initially, the total emissions are relatively low, reflecting conservative generation dispatch or minimal energy exchange. As iterations progress, the carbon emissions increase steadily, indicating a rise in energy generation to meet demand or maximize social welfare. This trend continues until it reaches a saturation point around iteration 85, beyond which emissions settle, signifying convergence in the system's generation strategy. The plot highlights the trade-off between economic optimization and environmental impact, emphasizing the importance of integrating carbon penalties to prevent excessive emissions during market optimization.

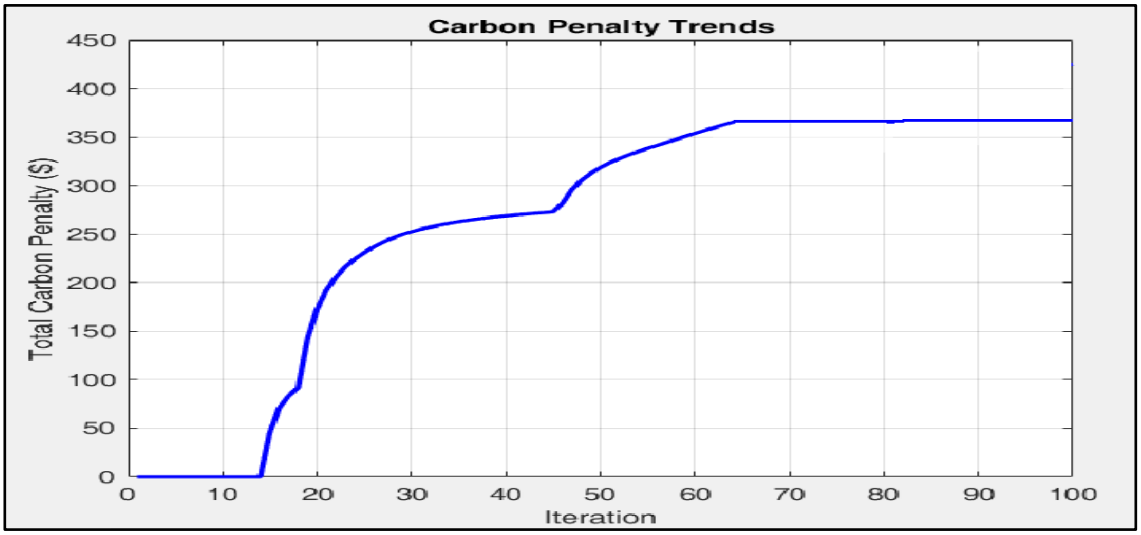

Figure 2.7: Carbon penalty trends over iterations

Initially, the penalty remains at zero, indicating that carbon emissions are within acceptable limits. However, as iterations progress, the penalty begins to rise steeply, reflecting that certain producers start exceeding their emission caps.

This increase suggests that the energy generation mix includes higher-emission producers, leading to penalties being applied. Around the mid-point of the iterations, the penalty curve begins to flatten, indicating that the system reaches a quasi-stable state where emissions stabilize, and no further significant increase in penalties is observed. This implies effective enforcement of carbon constraints in the system and reflects how pricing signals and penalties guide the market toward lower-emission behaviours over time.

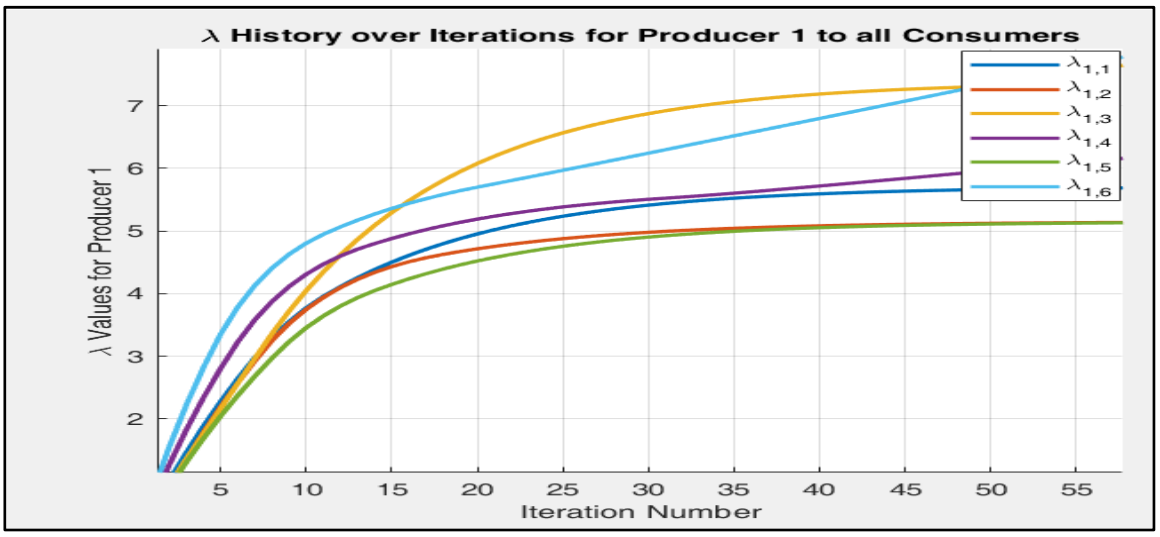

Figure 2.8(a): Energy trading price for producer1 to consumers

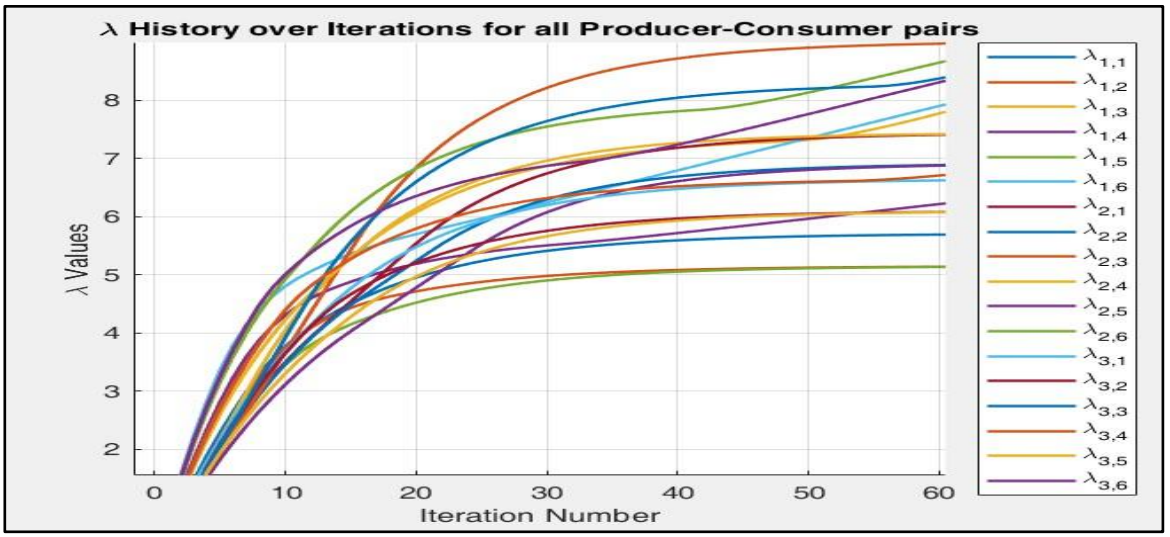

Figure 2.8(b): Energy trading prices for each producer-consumer pair

The transaction prices (λ values) evolve over iterations in a decentralized P2P energy trading environment. Each curve represents the dynamic pricing between a specific producer l and consumer m pair.

Initially, the λ values are set low and uniformly, indicating a starting point of minimal differentiation. As the iterations progress, each λ value adjusts based on supply-demand mismatches, cost preferences, and trading behaviour. The graph demonstrates how these values gradually converge, stabilizing after approximately 50 iterations. This convergence indicates that an equilibrium price is being established for each trading pair, ensuring market clearing and satisfaction of all trading constraints.

Overall, this graph validates the effectiveness of the iterative algorithm in dynamically updating prices to achieve optimal energy distribution among producers and consumers in the P2P market.

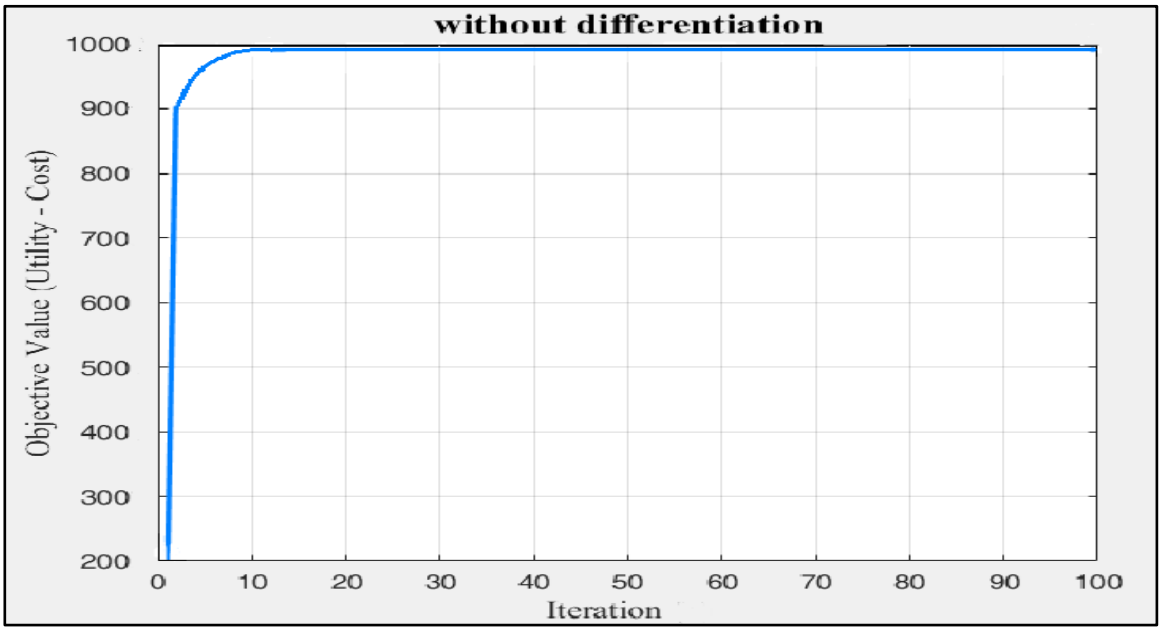

Figure 2.9: Total welfare without price differentiation

The graph illustrates the evolution of the objective function (defined as Utility − Cost) over the course of iterative updates in a P2P energy trading model without price differentiation. Initially, the objective value starts relatively low, indicating suboptimal trading arrangements. As the iterations progress, the value rapidly increases and stabilizes around 1000, signifying convergence to an optimal or near-optimal trading solution. This trend demonstrates that even in the absence of price differentiation, the iterative optimization process is effective in maximizing overall welfare by balancing generation costs and consumer utility. However, the flat plateau after convergence suggests limited flexibility or improvement beyond a certain point, which may be enhanced by introducing differentiated pricing or other advanced strategies.

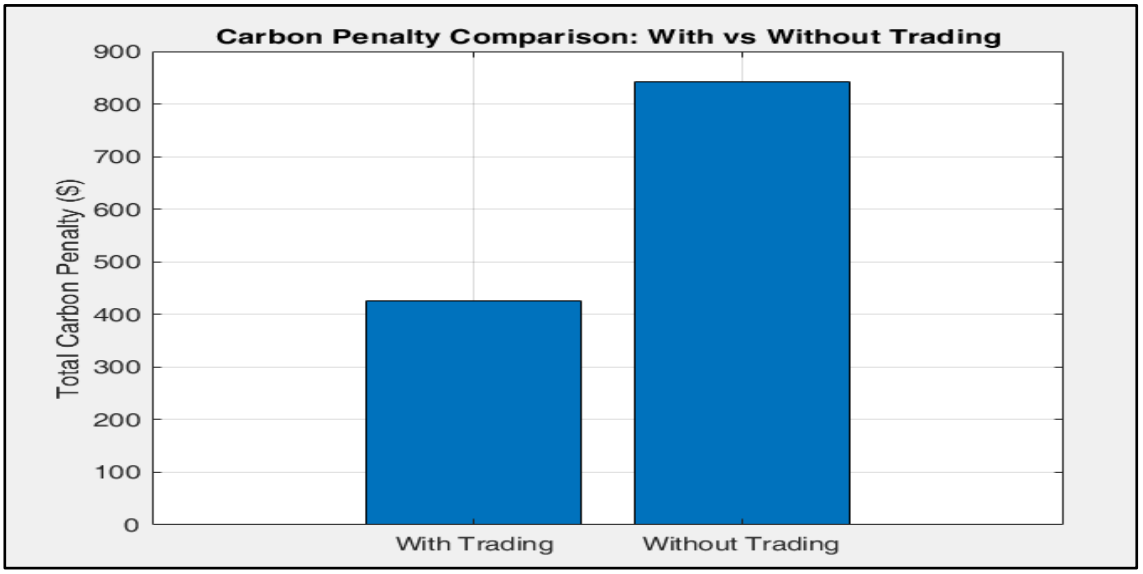

Figure 2.10: Comparison graph carbon penalty

The bar graph titled "Carbon Penalty Comparison: With vs Without Trading**"** illustrates the impact of P2P energy trading on total carbon penalty costs. It shows two distinct bars—one for the scenario with trading and the other without trading.

From the graph, it is evident that the total carbon penalty **is** significantly lower in the 'With Trading' case, amounting to approximately 420$, compared to the 'Without Trading' case, which incurs a penalty of over 820$. This substantial reduction in penalty costs demonstrates that P2P trading mechanisms encourage more efficient energy allocation among prosumers, leading to reduced carbon emissions and lower associated penalties.

In summary, the graph emphasizes the environmental and economic advantages of implementing decentralized P2P energy trading systems, particularly in terms of minimizing carbon penalties and promoting sustainable energy practices.

2.6 CONCLUSION

This chapter presents a decentralized peer-to-peer energy trading framework that incorporates price differentiation and carbon emission considerations within a smart grid environment. By simulating the IEEE 9-bus system, the model demonstrates how pricing and emission caps can influence trading behaviour, enhance social welfare, and reduce carbon emission. Simulation results validate the effectiveness of the proposed model in achieving fair energy distribution, reduced emissions, and improved market efficiency. It is found that total welfare increases to 49% using price differentiation. As also, the welfare is increased by 15$ which is 1% using carbon emission penalty.

CHAPTER 3

P2P ENERGY TRADING WITH RENEWABLE PRODUCER

3.1 INTRODUCTION

The rapid transformation of traditional power systems into decentralized and consumer-driven architectures has ushered in new challenges and opportunities in energy management. With the growing proliferation of distributed energy resources (DERs), particularly renewable sources such as solar and wind, the concept of peer-to-peer (P2P) energy trading has emerged as a promising model to enhance flexibility, autonomy, and efficiency in local energy markets.

In this context, the present study focuses on simulating a decentralized P2P energy trading framework that incorporates both economic optimization and technical constraints, with a particular emphasis on the integration of renewable generation. The trading environment consists of multiple energy producers and consumers engaging in bilateral energy transactions, where prices and power quantities are determined iteratively through decentralized negotiation. One of the producers in this framework is a renewable energy source. This inclusion reflects real-world grid modernization goals where renewables are expected to play a pivotal role in decarbonisation and cost reduction.

To achieve optimal trading, a Lagrangian-based distributed optimization algorithm is employed. Each market participant (producer or consumer) updates their generation or demand based on local objectives and a shared price signal (Lagrange multiplier λ). The algorithm iteratively adjusts these variables to maximize social welfare, which is defined as the difference between the total utility derived by consumers and the total cost incurred by producers. The presence of the renewable producer adds a new dimension to this optimization, offering low-cost energy that can enhance welfare but also introducing variability that must be managed within the market structure.

The simulation also integrates power transfer distance (PTD) factors to reflect the cost or effort required to deliver energy between geographically dispersed producers and

consumers. This adds a network-aware layer to the trading mechanism, ensuring that energy flows are not only economically optimal but also physically realistic in terms of delivery overhead and proximity-based pricing.

In addition, generation and demand constraints are strictly enforced through minimum and maximum bounds, and the price update mechanism includes Lagrange relaxation terms to ensure feasibility. The optimization process continues until convergence is achieved, measured by the stability of price updates across all trading pairs.

3.2 SYSTEM MODEL

This section outlines the mathematical and structural foundations of the decentralized peer-to-peer (P2P) energy trading model simulated in this study. The model captures interactions between multiple energy producers and consumers, where transactions are governed by dynamic price signals and constrained by technical and economic parameters. The framework is designed to simulate a realistic local energy market, incorporating a renewable energy producer alongside conventional generators.

As shown in below figure 3.1, producer 1 as renewable energy source and producer 2 & 3 as conventional generators for IEEE-9 bus system is presented.

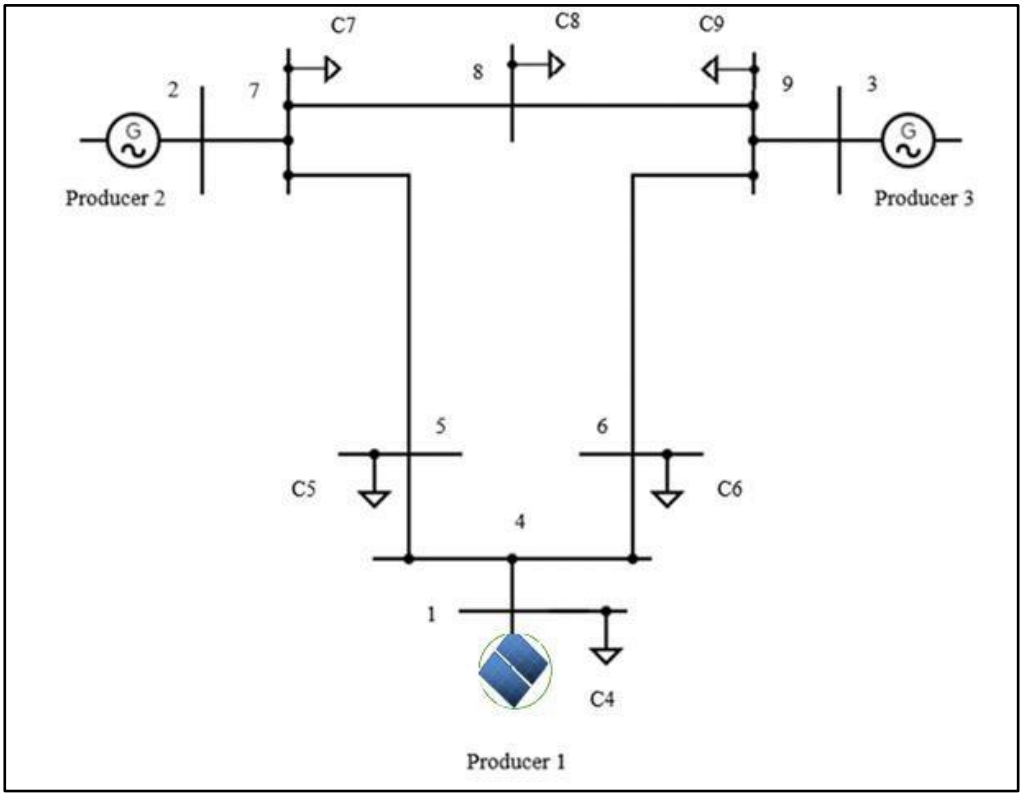

Figure 3.1: System model

3.2.1 MARKET PARTICIPANTS

The P2P trading market is composed of three energy producers. A set of producers $G_l = \{1,...,nG\}$ with an index $l \in G_l$ and a smart grid collection of customers with index $m \in Q_m$, where $Q_m = \{1,...,nQ\}$. $N = nG+nQ$ is the total number of players. Here, producer 1 is renewable energy source with zero marginal cost, representing wind or solar generation. Producer 2 & 3 are conventional generators with quadratic cost characteristics. The system consists of six energy consumers each having distinct demand profiles and utility preferences. Each producer is allowed to trade directly with each consumer through bilateral energy transactions.

3.2.2 DECISION VARIABLES

The decentralized P2P energy trading model revolves around three key decision variables that are updated at each optimization iteration:

- *G(l,m)*: Power supplied by producer *l* to consumer *m*
- *Q(m,l)*: Power demanded by consumer *m* from producer *l*
- *λ(l,m)*: Lagrange multiplier (interpreted as the local price between producer *l* and consumer *m*)

The variable *G(l,m)* represents the amount of electricity a producer generates and sells to a specific consumer. It depends on the generation capacity of producer *l* , the market clearing price for the transaction and the technical constraints like power limits and grid stability.

Each producer adjusts (*G(l,m))* dynamically based on market conditions, consumer demand, and price signals.

The variable *Q(m,l)* determines the amount of electricity a consumer purchases from a producer in a bilateral trade. It is influenced by the consumer's utility function, which reflects their willingness to pay for energy, price fluctuations in the market and the maximum – minimum demand limits ensuring the consumer does not exceed allowable consumption.

Each consumer selects (*Q(m,l)*) strategically, optimizing its demand based on price changes and available energy supply.

This variable *λ(l,m)* represents the dynamic trading price between producer (*l*) and consumer (*m*). It evolves through Lagrangian optimization, ensuring supply-demand balance, adjusts iteratively based on the difference between (*G(l,m))* and (*Q(m,l)*). Also, helps stabilize market efficiency by setting fair transaction prices.

Prices are updated using the dual decomposition approach [9, 10], where

$$\lambda_{lm}^{k+1} = \left\lceil \lambda_{lm}^{k} - \rho \left(G_{g,lm}^{k} - G_{d,ml}^{k} \right) \right\rceil^{+} \tag{3.1}$$

and rho is the step size that controls how fast prices adjust.

3.2.3 COST AND UTILITY FUNCTION

In the decentralized P2P energy trading model, producers generate electricity while consumers purchase energy based on price signals. To optimize energy allocation, we define cost functions for producers and utility functions for consumers. These mathematical models govern economic behaviour, ensuring fair transactions and efficient power distribution.

The producer cost function can be modelled as,

For conventional producers (such as thermal or hydro power plants), the cost function represents the expenses incurred in generating electricity. It is defined as[13]:

$$\Psi_{lm}(G_{g,lm}) = (a_l G_{g,lm}^2 + b_l G_{g,lm}) \tag{3.2}$$

Where:

- (a_l) and (b_l) are cost coefficients specific to producer (l).
- ($G(l,m)$) is the total power generated by producer (l).
- The quadratic term $a_l(G(l,m))^2$ models increasing marginal costs, reflecting higher fuel consumption at greater production levels.
- The linear term $b_l G(l,m)$ accounts for fixed generation costs.

Since each producer sells power to multiple consumers, total generation [13] is:

$$G_{g,l} = \sum_{m=1}^{nQ} G_{g,lm} \tag{3.3}$$

This ensures producers optimize their generation decisions based on demand and price signals along with the constraints [13] as follows,

$$G_{g,l}^{\min} \le G_{g,l} \le G_{g,l}^{\max} \tag{3.4}$$

The consumer utility function is modelled as,

Consumers [1] derive utility [11,12] from consuming electricity, capturing their satisfaction or willingness to pay. The consumer utility function is modelled as:

$$R_m\left(G_{d,m}\right) = \begin{cases} \delta_m G_{d,m} - \frac{1}{2} e_m G_{d,m}^2 & ;0 \le G_{d,m} \le \frac{\delta_m}{e_m} \\ \frac{\delta_m^2}{2e_m} & ;G_{d,m} \ge \frac{\delta_m}{e_m} \end{cases} \tag{3.5}$$

Where:

- δ_m is the initial willingness to pay per unit of power.
- e_m accounts for diminishing marginal utility, meaning additional energy is less valuable as consumption increases.
- ($G_{d,m}$) is the total power consumed by consumer (l), computed as:

$$G_{d,m} = \sum_{l=1}^{nG} G_{d,ml} \tag{3.6}$$

Each consumer adjusts ($G_{d,m}$) dynamically based on price signals and budget constraints, ensuring an efficient electricity market with following constraints [13],

$$G_{d,m}^{\min} \le G_{d,m} \le G_{d,m}^{\max} \tag{3.7}$$

Similarly, the cost function for renewable producer can be modelled as follows:

A renewable energy producer (such as solar or wind) has zero marginal cost, meaning it generates electricity without variable expenses. Its cost function is:

$$\Psi_{lm}(G_{g,lm}) = 0 \tag{3.8}$$

where:

- ($a_l = 0$, $b_l = 0$), implying no operational cost.
- The renewable generator injects a fixed or slightly varying amount of power each iteration.

Despite zero cost, renewable energy earns revenue in market transactions, ensuring economic sustainability. Producers aim to minimize costs while selling energy at competitive prices. Consumers maximize utility while adjusting purchases based on local price signals. Renewable energy integrates efficiently, reducing overall system costs.

3.2.4 TRADING CONSTRAINTS

In a decentralized peer-to-peer (P2P) energy trading model, each producer and consumer operates within predefined limits to ensure stable energy transactions and grid reliability. These constraints prevent unrealistic power generation or consumption that could disrupt the energy system.

Each energy producer (e.g., power plants, renewable sources) is bound by physical and economic constraints, ensuring they operate within safe and feasible margins:

$$G_{g,l}^{\min} \leq G_{g,l} \leq G_{g,l}^{\max} \tag{3.9}$$

Where,

$G_{g,l}^{min}$ is minimum generation limit, ensuring the producer maintains at least a baseline power output. $G_{g,l}^{max}$ is maximum generation capacity, defining the upper bound of

production based on equipment limits or market rules. $G_{g,l}$ is total power generated, summing all bilateral transactions. These limits are necessary because,

- Physical constraints: Generators (thermal, hydro, wind, solar) have operating limits beyond which they cannot function safely.
- Economic viability: Some producers may not want to operate at low power levels due to inefficiencies in fuel consumption.
- Grid stability: Excessive generation can overload transmission lines, causing frequency deviations or voltage instability.

Each energy consumer (households, businesses, factories) has specific power requirements but cannot consume beyond safe and affordable thresholds:

$$G_{d,m}^{\min} \leq G_{d,m} \leq G_{d,m}^{\max} \tag{3.10}$$

Where, $G_{d,m}^{min}$ is minimum demand requirement, ensuring each consumer gets at least their essential power needs. $G_{d,m}^{max}$ is maximum allowable consumption, preventing grid overload or excessive purchases beyond their budget. $G_{d,m}$ is total power consumed. These limits are necessary because,

- Avoiding shortages: Consumers need a guaranteed minimum power supply to prevent blackouts.
- Preventing excess demand: Consumers should not be allowed to purchase more than available capacity.
- Cost control: Some consumers may be restricted by budget constraints for electricity payments.

3.2.5 PRICE ADJUSTMENT MECHANISM

In peer-to-peer (P2P) energy trading, prices evolve iteratively through dual decomposition (Lagrangian optimization) to ensure a dynamic balance between energy supply and demand. This iterative process adjusts transaction prices locally for each trading pair, helping achieve a fair and efficient market equilibrium.

The lagrangian function for optimization can be defined as follows [9, 10],

$$L\left(G_{g,lm},G_{d,ml},\lambda_{lm},\chi_{l}^{\min},\chi_{l}^{\max},\chi_{m}^{\min},\chi_{m}^{\max},\right)=\sum_{m=1}^{nQ}\sum_{l=1}^{nG}R_{m}\left(G_{d,ml}\right)-\sum_{l=1}^{nG}\sum_{m=1}^{nQ}\lambda_{lm}(G_{g,ml})$$
$$+\sum_{l=1}^{nG}\sum_{m=1}^{nQ}\lambda_{lm}\left(G_{g,lm}-G_{d,ml}\right)+\sum_{m=1}^{nQ}\chi_{m}^{\min}\left(G_{d,m}-G_{d,m}^{\min}\right)+\sum_{m=1}^{nQ}\chi_{m}^{\max}\left(G_{d,m}^{\max}-G_{d,m}\right)$$
$$+\sum_{l=1}^{nG}\chi_{m}^{\min}\left(G_{g,m}-G_{g,m}^{\min}\right)+\sum_{l=1}^{nG}\chi_{m}^{\max}\left(G_{g,m}^{\max}-G_{g,m}\right)$$

(3.11)

The first order derivative is taken to obtain equation for lagrange variable[10]. The iterative price update equation is

$$\lambda_{lm}^{k+1}=\left[\lambda_{lm}^{k}-\rho\left(G_{g,lm}^{k}-G_{d,ml}^{k}\right)\right]^{+} \tag{3.12}$$

Where,

- (λ_{lm})= Updated price between producer (l) and consumer (m) in iteration ($k+1$).
- ($G_{g,lm}$) = Power supplied by producer (l) to consumer (m).
- ($G_{d,ml}$) = Power demanded by consumer (m) from producer (l).
- (ρ) = Step size, controlling how much the price adjusts per iteration.
- (k) = Current iteration index, meaning this equation is continuously updated.

The max(0, ...) ensures that prices remain non-negative (since energy prices cannot be negative in real markets). If ($G_{g,lm}$) > ($G_{d,ml}$), it means supply exceeds demand, leading to a price decrease. If ($G_{d,ml}$) < ($G_{g,lm}$), then demand exceeds supply, causing a price increase. Over multiple iterations, (λ_{lm}) settles to a stable value, achieving equilibrium. ρ determines how aggressively prices change per iteration. If ρ is too large, prices adjust too quickly, potentially leading to instability. If ρ is too small, price convergence takes longer. A carefully chosen ρ allows smooth convergence, ensuring that prices respond naturally to supply-demand fluctuations

This iterative update ensures that the energy market reaches equilibrium. Producers adjust their generation levels based on the updated price. The generation levels for producers and consumers can be obtained from (3.11) as follows,

$$\chi_l^{\min,k+1} = \left[\chi_l^{\min,k} - \rho\left(G_{g,l}^{k} - G_{g,l}^{\min,k}\right)\right]^{+} \tag{3.13}$$

$$\chi_l^{\max,k+1} = \left[\chi_l^{\max,k} - \rho\left(G_{g,l}^{\max,k} - G_{g,l}^{k}\right)\right]^{+} \tag{3.14}$$

$$\chi_m^{\min,k+1} = \left[\chi_m^{\min,k} - \rho\left(G_{d,m}^{k} - G_{d,m}^{\min,k}\right)\right]^{+} \tag{3.15}$$

$$\chi_m^{\max,k+1} = \left[\chi_m^{\max,k} - \rho\left(G_{d,m}^{\max,k} - G_{d,m}^{k}\right)\right]^{+} \tag{3.16}$$

3.2.6 OBJECTIVE FUNCTION

The optimization goal in a decentralized P2P energy trading system is to maximize total social welfare, ensuring economic efficiency and fairness while maintaining energy system stability. Social welfare [16] can be given by,

$$SW = \sum_{m=1}^{nQ}(R_m(G_{d,m}) - \sum_{l=1}^{nG}((\Psi_l(G_{g,l})) + Rr \tag{3.17}$$

Where,

- $R_m(G_{d,m})$ is consumer Utility, representing user satisfaction from electricity consumption.
- $(\psi_l(G_{g,l}))$ is producer Cost, representing generation expenses.
- Rr is revenue from renewable which is earnings of renewable producers, despite zero marginal cost.

3.2.7 CONVERGENCE CRITERIA

The peer-to-peer (P2P) energy trading algorithm operates iteratively, adjusting prices until market equilibrium is reached. The stopping criterion ensures that price changes stabilize, allowing transactions to be finalized in a fair and computationally efficient manner.

The algorithm stops when: ($max|\ \lambda(k+1) - \lambda(k)| < tolerance$) (3.18)

Where,

- ($\lambda(k)$) and ($\lambda(k+1)$) are the local trading prices at iteration (k) and ($k+1$).
- ($max|\ \lambda(k+1) - \lambda(k)|$) represents the largest price change between consecutive iterations.
- Tolerance is a predefined threshold ensuring price stabilization

If price differences become negligibly small, the market is stable, meaning supply matches demand, prevents unnecessary computations once optimal trading conditions are achieved, ensures fast execution, making the algorithm practical for real-time trading applications.

3.3 SIMULATION SETUP & CASE STUDY

This section outlines the technical and operational settings used to simulate the decentralized P2P energy trading model. The simulation was conducted in MATLAB and was designed to evaluate the impact of integrating a renewable producer into a decentralized market using Lagrangian-based optimization.

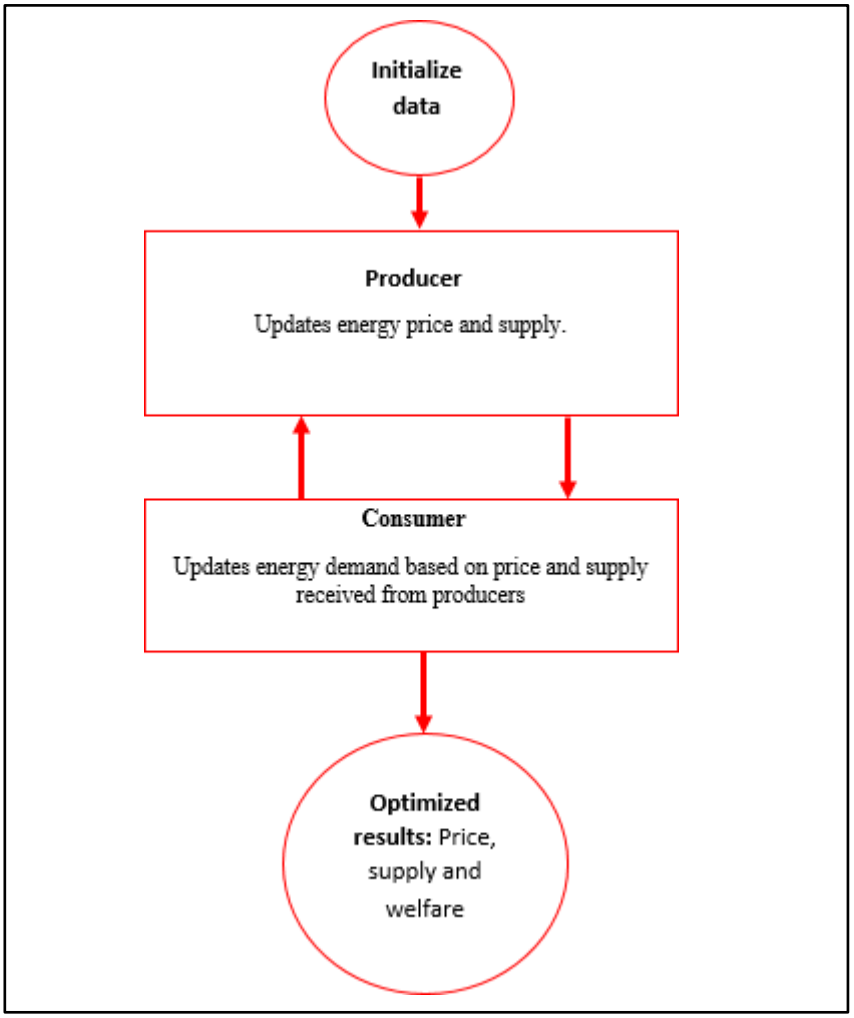
Initialize data
Producer
Updates energy price and supply.
Consumer
Updates energy demand based on price and supply received from producers
Optimized results: Price, supply and welfare

Figure 3.2: Implementation process

Table 3.1: Producer's input parameters

Producer	a_l	b_l	G_{gmin}	G_{gmax}
	($/MWh²)	***($/MWh)***	***(MWh)***	***(MWh)***
P_1	0	0	10	350
P_2	0.0062	4.20	20	290
P_3	0.0075	3.25	15	400

Table 3.2: Consumer's input parameters

Consumer	e_m	δ_m	G_{dmin}	G_{dmax}
	($/MWh^2)	***($/MWh)***	***(MWh)***	***(MWh)***
C_4	00.0720	08.25	060	150
C_5	00.0660	07.90	050	100
C_6	00.0700	07.55	090	145
C_7	00.0550	08.00	060	140
C_8	00.0750	07.75	050	150
C_9	00.0450	08.05	070	170

IEEE-9 bus system with six consumers and three producers are taken into consideration for case studies of the suggested approach, as seen in figure 2. Producers are situated at buses 1, 2 and 3 in IEEE 9 bus systems, where as consumers are positioned at buses 4 through 9. The sensitive information of producers and consumers are given in Table 1 and Table 2.

For updating the Lagrangian multiplier, a step size of 000.005 is chosen, $\alpha = 0.02$ and $\eta = 0.1$ are taken into consideration as the emission cost factors [16].

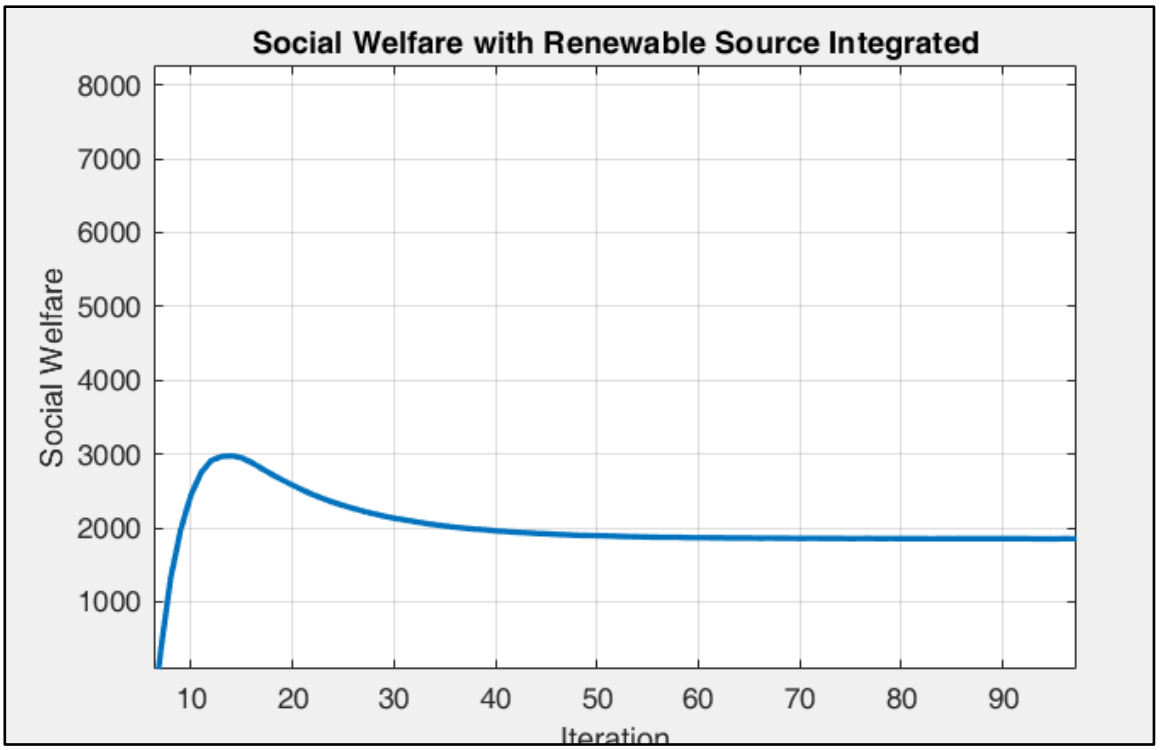

Figure 3.3: Social welfare with renewable source integrated

This graph in fig. 3.3 titled "Social Welfare with Renewable Source Integrated" represents the evolution of social welfare (i.e., the economic benefit of a peer-to-peer energy trading system) over iterations during the optimization process.

The X- axis shows the number of iterations in the decentralized energy trading algorithm. Each iteration updates the power generation, consumption, and pricing (Lagrange multipliers λ) to move towards optimality. Whereas, Y-axis reflects the net economic benefit of the entire system, including renewable energy.

During initial iterations from 1-15, there is a rapid increase in social welfare. This suggests early iterations significantly improve energy allocation and pricing between producers and consumers. At iteration 15, social welfare reaches a maximum (~3000). This may represent an optimal initial configuration where both utility and cost are temporarily well-aligned. Then, between iterations 15-40, the welfare begins to decline gradually, this could occur due to increased renewable supply being priced too low (due

to low marginal cost), causing an imbalance or inefficiency. After iteration 40, the curve flattens and stabilizes around a constant value of 1854$. The algorithm has converged to a steady state: demand, supply, and prices are balanced.

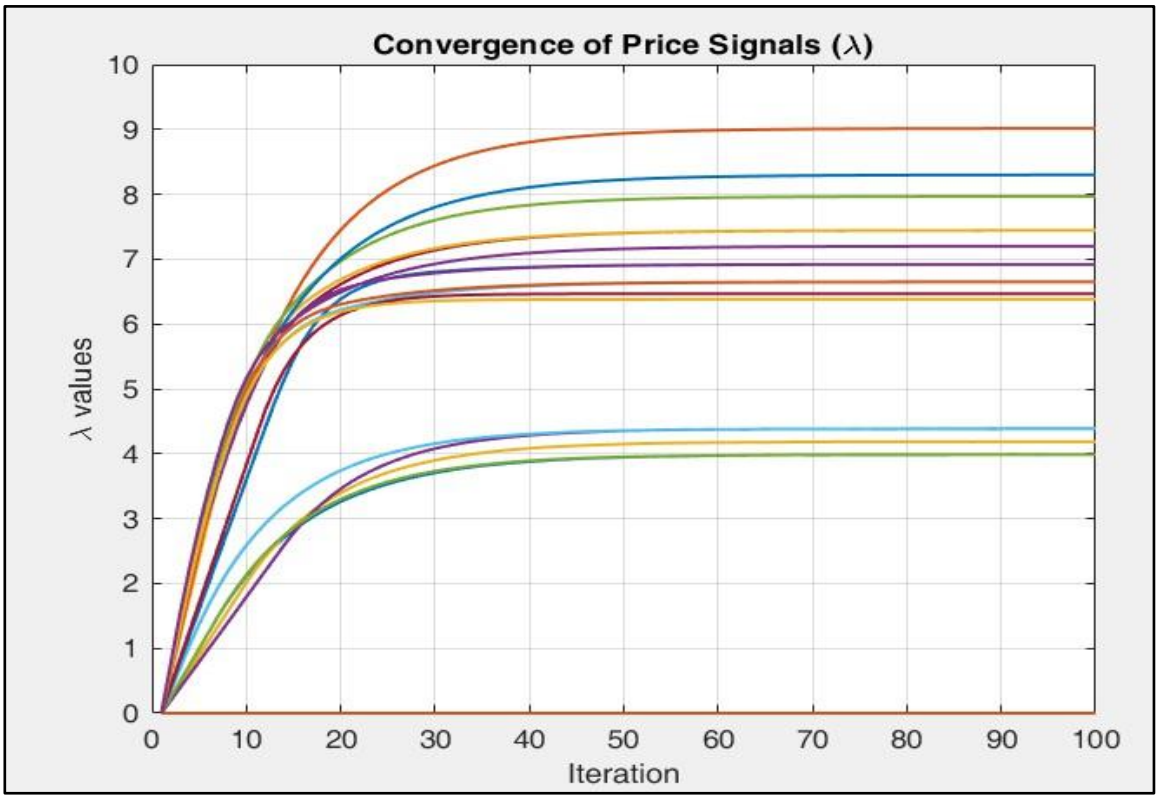

Figure 3.4: (a) Convergence of price signals λ

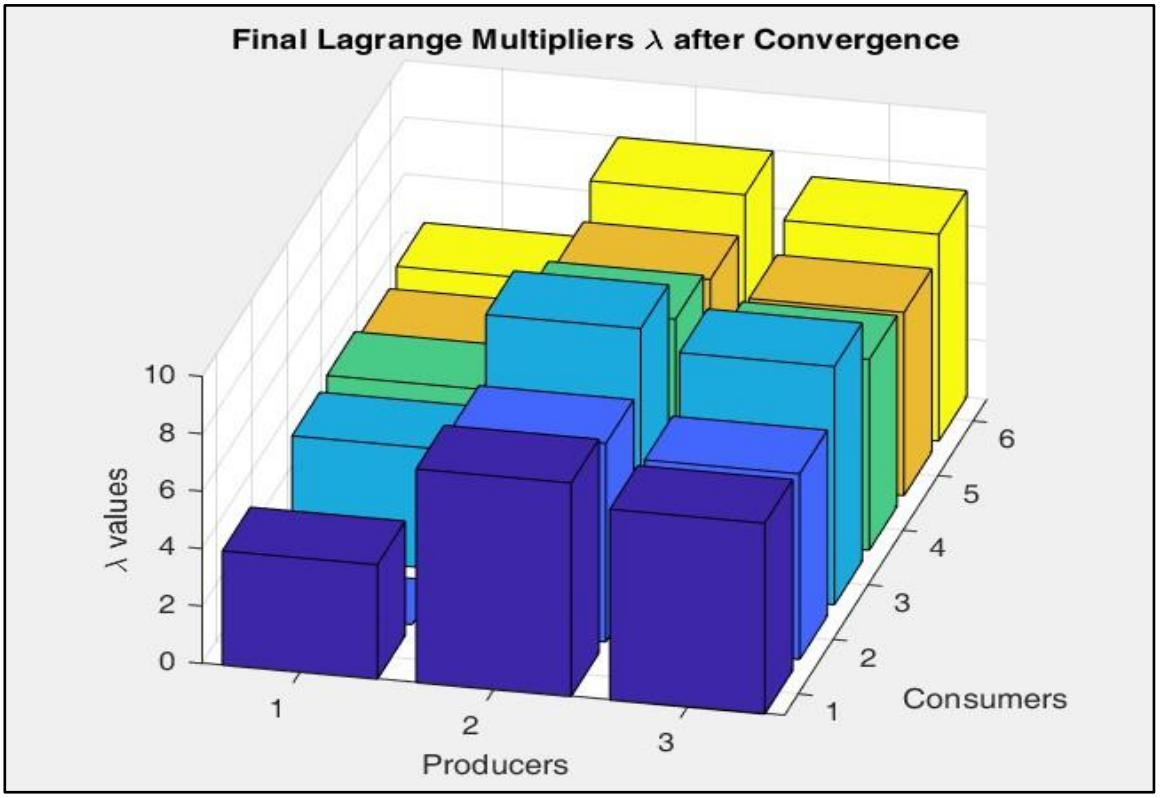

Figure 3.4: (b) 3-D view for values of λ for each producer-consumer pair

This graph illustrates the evolution of Lagrange multipliers (denoted as λ) over 100 iterations in a decentralized energy trading framework involving producers and consumers. The λ values represent the price signals or shadow prices that balance supply and demand between each producer–consumer pair. X-axis represents iterations which shows the number of iterations in the optimization loop (from 1 to 100). Whereas, Y-axis represents the updated price signals (λ) between producers and consumers. These are interpreted as the clearing prices in the peer-to-peer (P2P) energy market.

There are 18 individual curves, corresponding to the λ values between 3 producers × 6 consumers. During initial Values (Iteration 1) all λ values start from 0, which means no trade agreement (or price) is initially assumed between any producer and consumer. After, there is rapid Increase in early iterations, most λ values rise sharply within the first 10–20 iterations, indicating strong supply–demand mismatches and quick adjustments to meet constraints on energy generation and consumption. The λ curves begin to flatten after iteration 30-50, showing that the optimization is converging the market is reaching

equilibrium prices where supply ~ demand and the algorithm is minimizing the lagrangian (or welfare function).

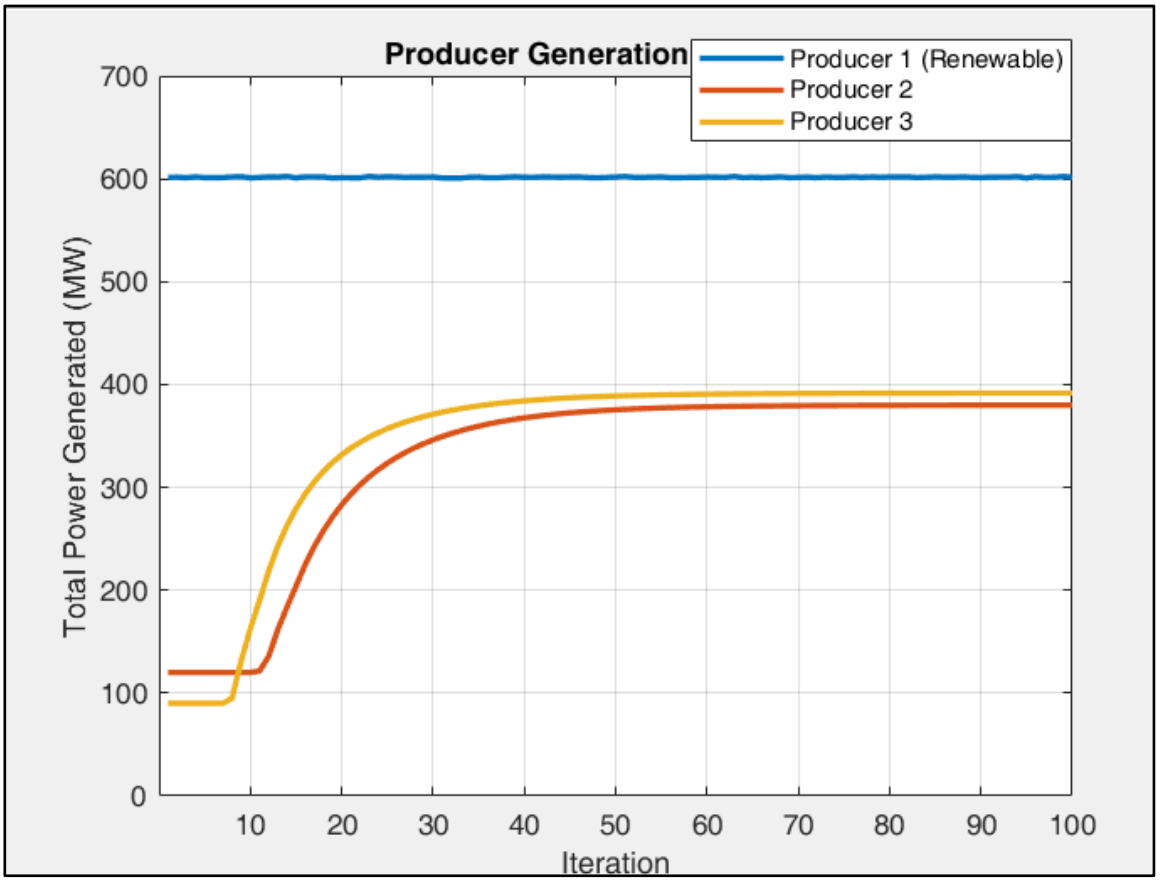

Figure 3.5: Total power generated by each producer

This graph shows how the total power generated by each producer in a P2P energy trading system evolves over 100 iterations of the decentralized optimization algorithm. The setup includes three producers, with Producer 1 being renewable (zero cost), and Producers 2 and 3 being conventional (thermal) units. X-axis represents the number of iterations in the decentralized optimization process (from 1 to 100).Y-axis shows the total power output in megawatts (MW) from each producer (i.e., sum of energy supplied to all consumers by that producer) across iterations.

Producer 1 is renewable which remains nearly flat at 600MW. The graph indicates that the renewable generator is supplying maximum or steady power regardless of price signal

since its cost is zero. This reflects a non-price sensitive nature, which is typical for renewable energy sources. Producer 2 & 3 are thermal generators which increases gradually. Producer 2 starts low (~120MW) and increases gradually during early iterations and reaches around 370MW. This indicates producer 2 is adjusting its generation based on increasing λ values, converging to its economically optimal output. Producer 3 follows a similar trend reaching a slightly higher final value (~390MW).

3.4 CONCLUSION

This chapter presents the key outcomes and insights derived from the implementation and simulation of a decentralized Peer-to-Peer (P2P) energy trading framework incorporating renewable energy generation and lagrangian-based optimization. The system is designed to reflect the real-world dynamics of local energy markets where producers and consumers engage in bilateral energy transactions under physical and economic constraints.

Producer 1 (renewable) consistently delivered high and stable power output, reflecting its fixed generation profile. Despite zero operational cost, the renewable producer generated revenue through trade with consumers, validating the economic sustainability of renewables in decentralized energy markets.

A significant outcome of this simulation was the maximization of social welfare, defined as the difference between consumer utility and producer cost. Initially, welfare increased rapidly, peaking early in the iteration process, followed by stabilization. The inclusion of the renewable generator contributed to higher welfare by providing very low cost electricity, which reduced the overall generation cost in the system. The final welfare value stabilized around 1854 $, indicating a balanced and efficient energy market. This welfare is (1854-1625=229) $ more than that of without integration of renewables (in fig. 2.4) which is 12.35% more, thus, increasing social welfare.

CHAPTER 4

CONCLUSION

4.1 Summary

This thesis presented a comprehensive study on decentralized Peer-to-Peer (P2P) energy trading integrated with network constraints, carbon emission penalties, and renewable energy generation, using the IEEE 9-bus system as a case study. The focus was on optimizing social welfare while incorporating environmental and infrastructural realities of power systems.

The study was conducted in two major parts:

Chapter 2 contributed to network-aware decentralized energy trading with carbon penalties. A decentralized P2P energy trading framework was developed based on lagrangian relaxation. The model included constraints such as, maximum and minimum generation and load capacities, Power Transfer Distance (PTD) between producer and consumer pairs, carbon emission caps with a logarithmic penalty function for exceeding the allowed emission levels. The carbon penalty function discouraged over-dependence on fossil-fuel-based producers while promoting cleaner energy usage. Social welfare was defined as the difference between consumer utility and producer costs (including carbon penalties and network losses). The findings of this chapter includes social welfare that increased steadily over iterations and reached a converged value, indicating successful optimization. Reduction of carbon emissions and carbon penalties under the trading scenarios. The system promoted fairness and efficiency while respecting grid limitations and environmental constraints.

Chapter 3 of the thesis introduced a renewable energy producer (Producer 1) with zero generation cost and no emissions. A modified utility-cost optimization approach was implemented, accounting for dynamic generation of the renewable producer, reduced carbon penalties due to cleaner production, adaptive Lagrange multipliers (λ) governing bilateral trades. Plots were generated for welfare, generation patterns, consumer demand,

and convergence of price signals (λ). The finding of this chapter inclues total social welfare improved by approximately 12.35% with the inclusion of the renewable producer, demonstrating its economic value. The renewable producer consistently contributed to the energy supply, proving the feasibility and stability of renewable integration. The simulation showed faster convergence in λ values, enhancing real-time applicability. A comparison between “with trading” and “without trading” scenarios showed significant benefits in welfare, reduced carbon emissions, and reduced penalties.

4.2 Scope for future work

Despite promising results in chapter 3 for renewables, battery storage systems are yet not modelled explicitly. The renewable’s producer profile may add actual wind generated energy data from real word instead only relying on solar. By adding storage systems, the effectiveness of model can be increased. Also, in chapter 4, blockchain based trading platforms can be added with real time pricing models like time of use tariff and dynamic incentive mechanism can be implemented.

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